Deep Learning for Model-Free Prediction of Thermal States of Robot Joint Motors

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Abstract: In this work, deep neural networks made up of multiple hidden Long Short-Term Memory (LSTM) and Feed Forward layers are trained to predict the thermal behavior of the joint motors of robot manipulators. A model-free approach is adopted. It allows for the accommodation of complexity and uncertainty challenges that might compromise the derivation, identification, and validation of a large number of parameters of an approximation model that is hardly available. To this end, sensed joint torques are collected and processed to foresee the thermal behavior of joint motors. Promising prediction results of the machine learning based capture of the temperature dynamics of joint motors of a redundant robot with seven joints are presented.

Keywords: Robotics, Thermal Management, Artificial Intelligence / Machine Learning.

1. INTRODUCTION

Robots are commonly used to unrelentingly achieve repetitive and hazardous tasks in industry and society. Meanwhile, they increasingly and skillfully assist and augment humans. Included are dynamic applications with a pronounced level of physical interactions between humans and robots, such as using a robot as a companion (Basha (2025)), home-helper and caregiver (Tsui et al. (2025),Gkiolnta et al. (2025)), as well as a prosthesis (Kim et al. (2025)). In this respect, large joint accelerations, high payload manipulations, and motions with specific configurations (see, e.g., Fig. 1) can induce an overheating of joint motors of robots. An excessive motor temperature can accelerate the degradation of insulation materials and reduce the motor efficiency (Yehorov et al. (2025)) along with jeopardizing the positioning accuracy of the robot because of axial deformations and drifts (Soga et al. (2024)).

Most robot manufacturers, including Franka, Kinova, and KUKA, offer built-in functions to shut down the robot once a critical temperature threshold is attained. Whereas this functionality is advantageous to preserve the performance and reliability of motors and surrounding electronic components, an undesired shutdown is likely to compromise the robot availability for production and assistance purposes. This situation gets exacerbated as the robot is not equipped with mechanical breaks as in Fig. 1. In this case, critical collisions with the environment might occur, endangering human beings or leading to hardware (i.e., robot, workpiece, workcell, etc) damages. Furthermore, thermal burns represent not only a severe safety issue in physical human-robot-interaction but also a hindrance for elevated user experience that is necessary to engage and sustain a symbiosis between humans and robots.

Predicting the thermal behavior of robot joints is an essential step toward the development of countermeasures that help anticipate overheating, preserve the robot availability, prolong its lifetime, and improve its usability. The Industry 4.0, Industry 5.0, Society 5.0, and Society 6.0 realms are likely to benefit from this capability. This is because it propels operational efficiency through intelligent thermal management of the robot for availability purposes. It also supports decent and sustainable haptic working conditions for the workforce, as well as human-centered robotized servicing for comfortable smart living and social well-being in different ecosystems. Meeting such goals requires an approach that can turn robot diversity and application uncertainties into competitive advantages in terms of flexibility, insights, transferability, and scalability.

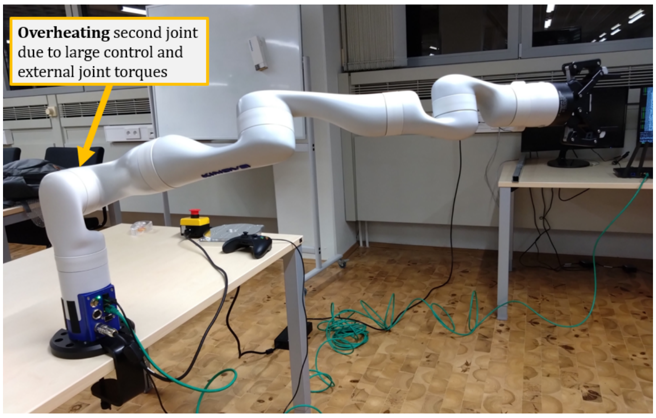

Fig. 1. Robot posture increasing a motor temperature.

This work predicts the thermal behavior of joint motors of robots with the following key contributions. The prediction approach is

- data-driven, paving the ground for an insightful, non-invasive, and inclusive operationalization in real-time. The approach therefore follows design objectives of

our overarching Metarobotics framework (Kaigom (2023)). In our previous work (Abt et al. (2025)), the thermal behavior of robots is sensed and virtually made accessible to even novices through immersive, dynamic, and intuitive monitoring and control driven by digital twins (Kaigom and Roßmann (2020)). Since most robots do not output temperature data, we extend our previous work by capturing their thermal motor behavior from observed actuation profiles.
- model-free through the development of a deep learning-based framework that leverages multiple hybrid layers to learn the underlying thermal dynamics of joints from sensed data commonly available via application programming interfaces (APIs). It is worth noting that no system-related parametric or actuation profile assumptions are made. These particularities are useful to avoid model complexity while fostering generalization and transferability to other robot types regardless of the number and type of joint motors.
- evaluated on data collected from a redundant robot with seven joints.

2. RELATED WORKS

Predicting the temperature behavior of robot motors has attracted attention in the recent years. Online learning of thermal model parameters of a such motor is carried out in Kawaharazuka et al. (2020). The goal is a precise forecasting of the motor core temperature of musculoskeletal humanoid robots. An enhanced model allows to predict maximum output motor torques. Anomalous behaviors are detected by analyzing variations of thermal dynamics. Thermal control is developed to limit the tensions in the actuation of the musculoskeletal humanoid. In order to safely operate a motor at torques which are considerably larger than its rated torques, Singh et al. (2021) capture and regulate core temperatures via current control. To this end, a thermal abstraction model is developed and employed to design the thermal controller. The goal is to keep the stator temperature below a heating threshold while avoiding risks of high torques. A method is proposed to control the maximum limit of the current to this end. A forced cooling approach is applied to influence the thermal resistance, steady-state current, and output torque. However, cooling strategies might be challenging to implement once the robot is in use potentially in toughly accessible environments (e.g., space orbits). In this case, intelligent thermal management approaches are helpful.

Afaq et al. (2023) focus on thermal management of robotic applications under extreme temperatures. Electronics heating and cooling are considered. A temperature control driven by fuzzy logic is developed and demonstrated to this end. Decreases of extreme high temperature from $50°$ to $8°$ are shown. Fan-based forced convection is used to cool electronics. Excessive internal temperatures in a permanent magnet synchronous motor (PMSM) taking non-stationary loads, which might lead to a reduction of its life time, is addressed in Chen et al. (2024). An accelerated degradation model is derived to evaluate the reliability function and predict the lifetime of the PMSM under thermal stress. Geometric backlash and temperature-related drift errors in joints of industrial robots are compensated in Sigron et al. (2023). A model that reflects the thermal expansion of links is developed and used for thermal expansion correction. LSTM Neural Networks (He et al. (2024)) and Pseudo-Siamese Nested LSTM (Cai et al. (2021)) are employed to predict the temperature in Permanent Magnet Synchronous Motors. A trapezoidal torque profile is employed in He et al. (2024) whereas the torque dynamics is not released in (Cai et al. (2021)). A thermal recovery of robot joints is achieved in Jorgensen et al. (2019). To this end, the thermal dynamics is captured as a first order ordinary differential equation subject to constant positive and negative step-like profiles of joint torques. The exponential-based dynamics of the temperature behavior is derived. A parameter identification is carried out to demonstrate the performance of the model for step-like joint torques. Another model-based approach is proposed in Trinh et al. (2023) to predict temperature-dependent joint frictions in industrial robots.

Contributions mentioned thus far are mostly model-driven. They fit with specific robots provided that parameters have been identified in advance. However, parameter identification requires noise robustness and low sensitivity (Zhang et al. (2024), de Hoyos Fernández de Córdova et al. (2024)), which might be a time consuming analysis task prone to additional uncertainties due to unseen/unmodeled/truncated dynamics (Shang et al. (2024)). Sometimes, such a process must be repeated from scratch for a given new robot, which inhibits quick and large scale automation involving multiple robots in terms of complexity, workload, and costs. As the robot is hardly accessible, such as in space servicing, identification tasks might be hard to complete because of limited access to pertinent (e.g., excitation) data. Autonomous task completion without human interventions, as expected by Industry 6.0, calls for machine learning-embedded solutions (Carayannis et al. (2024)) that can extend the robot intelligence for self-condition monitoring. The approach proposed in this work also falls into this category. Robot datasets available from standard APIs are harnessed to predict the thermal behavior of its joint motors. Trained machine learning models can be executed by dedicated services of digital twins with the physical robot is embedded to detect, communicate to other entities, and anticipate detrimental thermal issues. In contrast to related works, no restriction is made on robot types, number of joints, and actuation profiles.

3. DATA-DRIVEN PREDICTION OF THERMAL JOINT STATES

For submission guidelines, follow instructions on paper submission system as well as the event website.

Note that the 8^{th} IFAC Symposium on Mechatronic Systems and 11^{th} IFAC Symposium on Nonlinear Control Systems impose a strict page limit of 6 pages for full contributions, so it will be better for you to prepare your initial submission in the camera ready layout so that you will have a good estimate for the paper length. Additionally, the effort required for final submission will be minimal.

3.1 Equations

Some words might be appropriate describing equation (1), if we had but time and space enough.

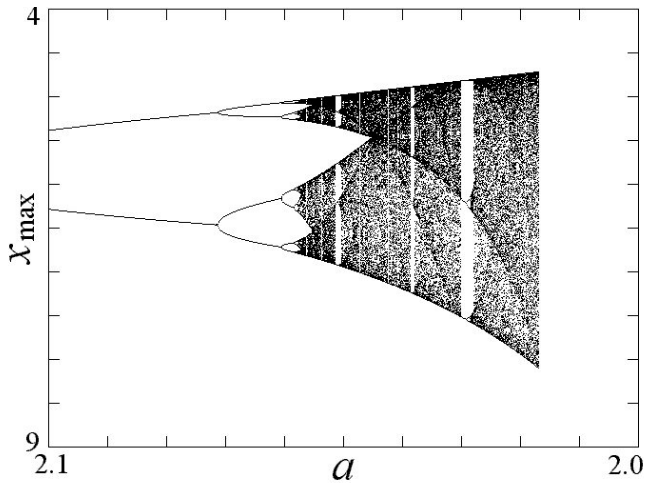

Fig. 2. Bifurcation: Plot of local maxima of x with damping a decreasing

$$\frac{\partial F}{\partial t} = D\frac{\partial^2 F}{\partial x^2}. \tag{1}$$

See Able (1956), Able et al. (1954), Keohane (1958) and Powers (1985).

Example. This equation goes far beyond the celebrated theorem ascribed to the great Pythagoras by his followers.

Theorem 1. The square of the length of the hypotenuse of a right triangle equals the sum of the squares of the lengths of the other two sides.

Proof. The square of the length of the hypotenuse of a right triangle equals the sum of the squares of the lengths of the other two sides.

Of course LaTeX manages equations through built-in macros. You may wish to use the `amstex` package for enhanced math capabilities.

3.2 Figures

To insert figures, use the `graphicx` package. Although other graphics packages can also be used, `graphicx` is simpler to use. See Fig. 2 for an example.

Figures must be centered, and have a caption at the bottom.

3.3 Tables

Tables must be centered and have a caption above them, numbered with Arabic numerals. See table 1 for an example.

Table 1. Margin settings

Page	Top	Bottom	Left/Right
First	3.5	2.5	1.5
Rest	2.5	2.5	1.5

3.4 Final Stage

Authors are expected to mind the margins diligently. Papers need to be stamped with event data and paginated

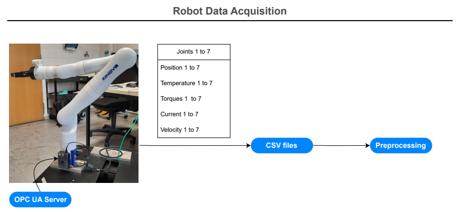

Fig. 3. Kinova data aquisition via OPC UA Server

for inclusion in the proceedings. If your manuscript bleeds into margins, you will be required to resubmit and delay the proceedings preparation in the process.

Page margins. See table 1 for the page margins specification. All dimensions are in *centimeters*.

3.5 PDF Creation

All fonts must be embedded/subsetted in the PDF file. Use one of the following tools to produce a good quality PDF file:

PDFLaTeX is a special version of LaTeX by Han The Thanh which produces PDF output directly using Type-1 fonts instead of the standard `dvi` file. It accepts figures in JPEG, PNG, and PDF formats, but not PostScript. Encapsulated PostScript figures can be converted to PDF with the `epstopdf` tool or with Adobe Acrobat Distiller.

Generating PDF from PostScript is the classical way of producing PDF files from LaTeX. The steps are:

(1) Produce a `dvi` file by running `latex` twice.
(2) Produce a PostScript (`ps`) file with `dvips`.
(3) Produce a PDF file with `ps2pdf` or Adobe Acrobat Distiller.

3.6 Copyright Form

IFAC will put in place an electronic copyright transfer system in due course. Please *do not* send copyright forms by mail or fax. More information on this will be made available on IFAC website.

4. DATA ACQUISITION AND PREPROCESSING

- Kinova Gen3 7 DoF Robot
- OPC UA Server and Client (data: pos, temp, torques, velocities and current), create Figure
- randomly generated (restrcited) joint angles/trajectories
- (reference to streamlit app?)
- Fit function with collected data?
- description of data preprocessing for LSTM and FF

5. PROPOSED MODELS (VARIOUS LSTMS, FEEDFORWARD) [AND COMPARISION?]

- various LSTMs (Strcuture: Hyperparameter Learning Rate, Epochs, Batch Size, no. of Layers, Regularization, adam optimization, RMSE, True vs Predicted Temps, etc.)
- FeedForward (same as above)
- fitted function?
- Comparisions

5.1 Figures and Tables

Figure axis labels are often a source of confusion. Use words rather than symbols. As an example, write the quantity "Magnetization", or "Magnetization M", not just "M". Put units in parentheses. Do not label axes only with units. For example, write "Magnetization (A/m)" or "Magnetization (Am^{-1})", not just "A/m". Do not label axes with a ratio of quantities and units. For example, write "Temperature (K)", not "Temperature/K".

Multipliers can be especially confusing. Write "Magnetization (kA/m)" or "Magnetization (10^3A/m)". Do not write "Magnetization (A/m) × 1000" because the reader would not know whether the axis label means 16000 A/m or 0.016 A/m.

5.2 References

Use Harvard style references (see at the end of this document). With LaTeX, you can process an external bibliography database using `bibtex`,[1] or insert it directly into the reference section. Footnotes should be avoided as far as possible. Please note that the references at the end of this document are in the preferred referencing style. Papers that have not been published should be cited as "unpublished". Capitalize only the first word in a paper title, except for proper nouns and element symbols.

5.3 Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even after they have already been defined in the abstract. Abbreviations such as IFAC, SI, ac, and dc do not have to be defined. Abbreviations that incorporate periods should not have spaces: write "C.N.R.S.", not "C. N. R. S." Do not use abbreviations in the title unless they are unavoidable (for example, "IFAC" in the title of this article).

5.4 Equations

Number equations consecutively with equation numbers in parentheses flush with the right margin, as in (1). To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Use parentheses to avoid ambiguities in denominators. Punctuate equations when they are part of a sentence, as in

[1] In this case you will also need the `ifacconf.bst` file, which is part of the `ifaconf` package.

$$\begin{aligned}\int_0^{r_2} F(r,\varphi)drd\varphi = [\sigma r_2/(2\mu_0)] \\ \cdot \int_0^{\inf} exp(-\lambda|z_j - z_i|)\lambda^{-1}J_1(\lambda r_2)J_0(\lambda r_i)d\lambda\end{aligned} \tag{2}$$

Be sure that the symbols in your equation have been defined before the equation appears or immediately following. Italicize symbols (T might refer to temperature, but T is the unit tesla). Refer to "(1)", not "Eq. (1)" or "equation (1)", except at the beginning of a sentence: "Equation (1) is ...".

5.5 Other Recommendations

Use one space after periods and colons. Hyphenate complex modifiers: "zero-field-cooled magnetization". Avoid dangling participles, such as, "Using (1), the potential was calculated" (it is not clear who or what used (1)). Write instead: "The potential was calculated by using (1)", or "Using (1), we calculated the potential".

A parenthetical statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.) Avoid contractions; for example, write "do not" instead of "don' t". The serial comma is preferred: "A, B, and C" instead of "A, B and C".

6. APPLICATION

Use the t option for the alignment of the subfigures:

7. DISCUSSION?

?

8. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

ACKNOWLEDGEMENTS

Place acknowledgments here.

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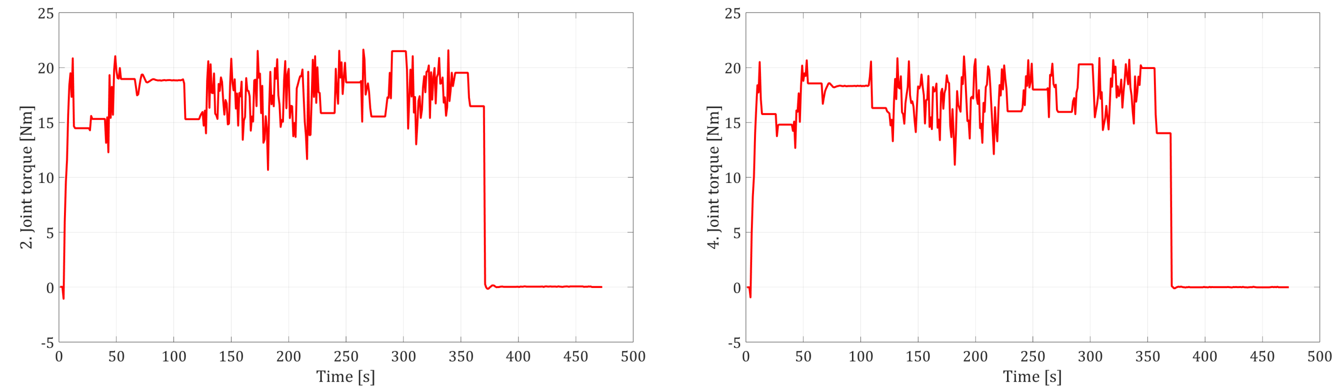
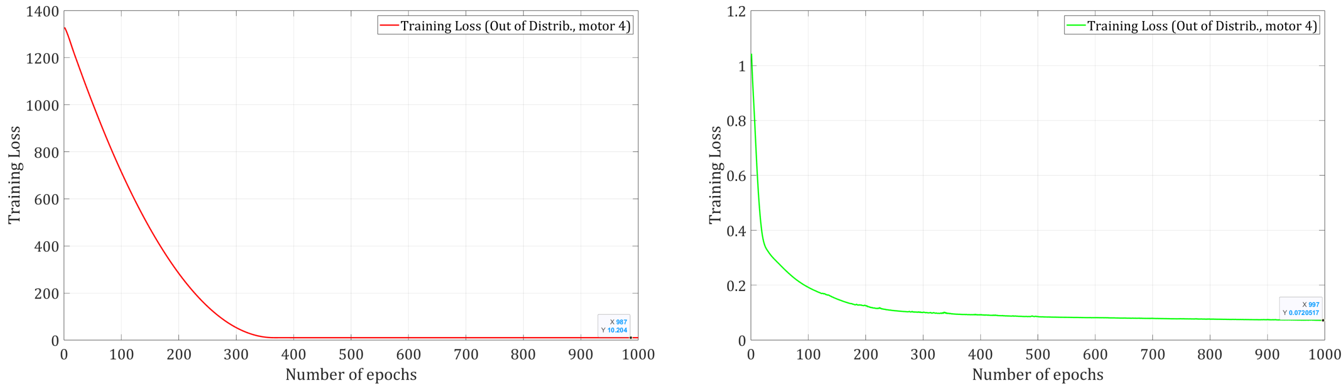


(a) Torque profile of the 2. motor.

(b) Torque profile of the 4. motor.

Fig. 4. Two different non-trivial torque profiles of the robot in Fig. 1. Observe that the profiles go beyond step functions.



(a) Training loss without data normalization.

(b) Training loss with z-score data normalization.

Fig. 5. Enhanced convergence velocity and effectiveness of the training loss through data normalization.

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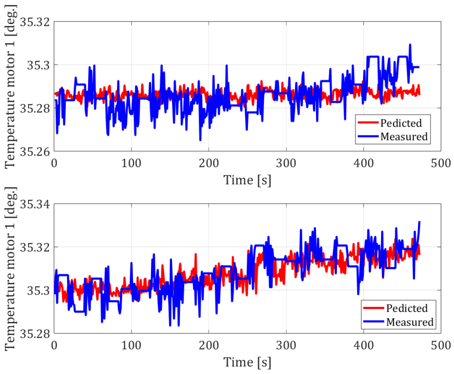
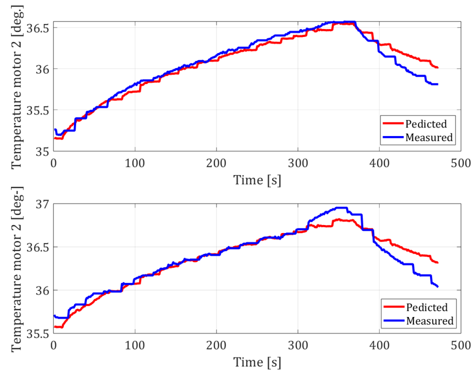
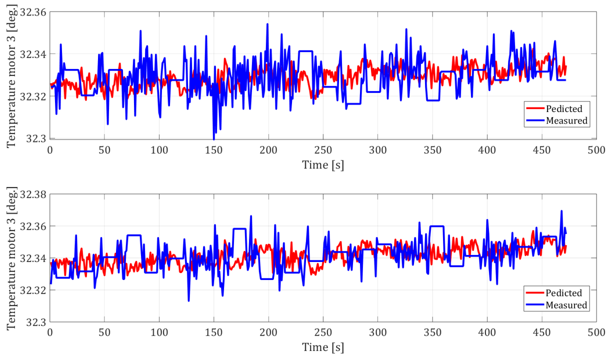


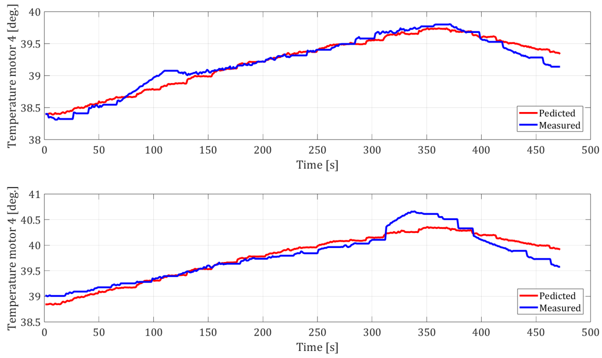
(a) Motor 1: Different predictions with **unseen** joint torques.



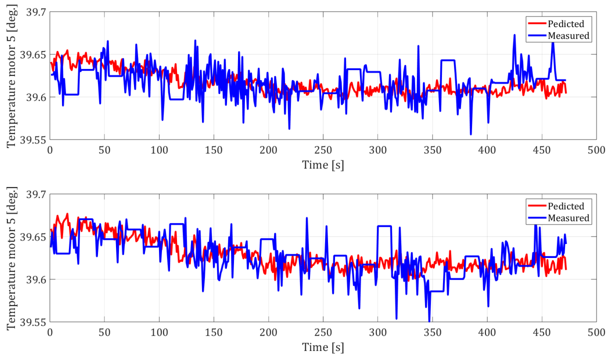
(b) Motor 2: Different predictions with **unseen** joint torques.



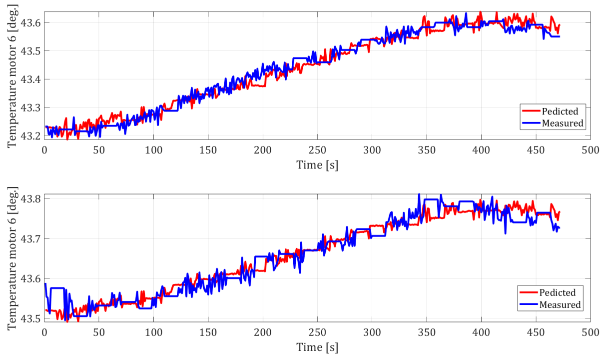
(c) Motor 3: Different predictions with **unseen** joint torques.



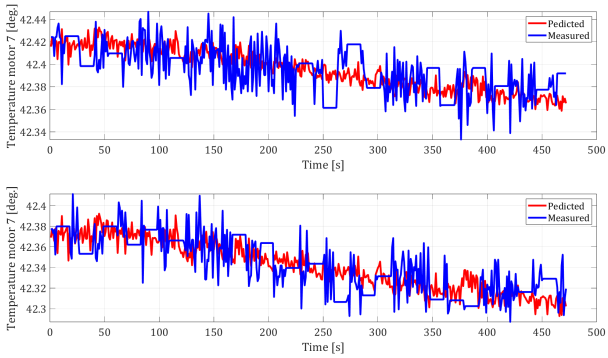
(d) Motor 4: Different predictions with **unseen** joint torques.



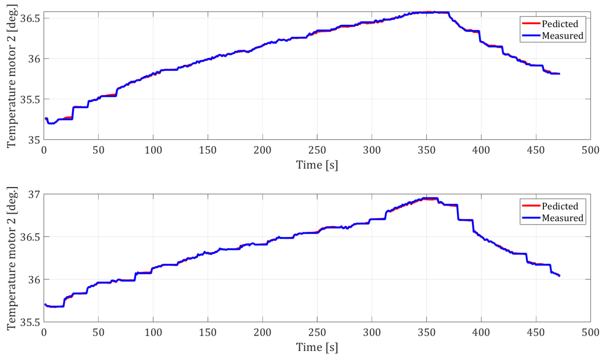
(e) Motor 5: Different predictions with **unseen** joint torques.



(f) Motor 6: Different predictions with **unseen** joint torques.



(g) Motor 7: Different predictions with **unseen** joint torques.



(h) Motor 2: Different predictions with **seen** joint torques.

Fig. 6. Capturing the thermal behavior of joint motors of the robot in Fig. 1 with previously unseen and seen data.

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Appendix A. A SUMMARY OF LATIN GRAMMAR

Appendix B. SOME LATIN VOCABULARY